Forecast Performance of Futures Price Models for Corn, Soybeans, and Wheat

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A futures price forecasting model is presented which uses monthly futures prices, cash prices received, basis values (cash prices less futures), and marketing weights to forecast the season-average farm price for U.S. corn, soybeans, and wheat. Accuracy of model forecasts are examined using standard measures, such as mean absolute percentage error (MAPE) and root mean squared percentage error (RMSPE). Tests for statistical differences between the futures model forecast and price projections from World Agricultural Supply and Demand Estimates (WASDE), are conducted using the modified Diebold-Mariano test statistic. Forecast encompassing tests are conducted to determine whether the futures model forecasts would benefit by combining them with WASDE projections. Forecast encompassing tests identified several periods where the combination of the two forecast methods would provide a better forecast than the futures model forecasts and so futures model forecast efficiency was rejected during these periods based on the necessary condition.

Key words: U.S. futures prices for corn, soybeans, and wheat, U.S. producer prices received for corn, soybeans, and wheat, basis values (price received less futures), marketing weights, forecast accuracy, futures market efficiency.

Price forecasts are critical to market participants making production and marketing decisions and to policymakers who administer commodity programs and assess the market impacts of domestic or international events. Price information has become even more important for market participants due to changes in U.S. agricultural policy. Passage of the 2002 Farm Act provides domestic support programs that are linked to the season-average price, such as the counter-cyclical program. Consequently, both producers and policymakers have a renewed interest in forecasts of the season-average price and its implications for the counter-cyclical payment rate.

The U.S. Department of Agriculture analyzes agricultural commodity markets on a monthly basis and publishes current year market information, including price projections (except for cotton), on a monthly basis in *World Agricultural Supply and Demand Estimates* (WASDE) (USDA d). The monthly WASDE price projection, for a given commodity, provides information that can be used by market participants and policymakers to keep abreast of season-average prices and the implied counter-cyclical payment rate.

Futures prices are a composite indicator of expected supply and use and thus can be used to forecast short-run farm prices (Danthine 1978, Gardner 1974, Peck 1976, and Tomek 1997). Tomek, (p. 42) states that “futures prices can be viewed as forecasts of maturity-month prices and the evidence suggests that it is difficult for structural or time-series econometric models to improve on the forecasts that futures markets provide.” Although a futures price may be an unbiased forecast, the variance of forecast error may be large, and increases with the forecast horizon. Therefore, accurate price forecasts are a challenge, especially for more distant time periods.

Hoffman (1991) developed a futures price forecasting model that provides weekly or monthly forecasts of the season-average price and more recently Hoffman (2005) (2007) extended this model to forecasting the counter-cyclical payment rate for corn, soybeans, and wheat. Participants from both the domestic and foreign commodity markets are keenly interested in this futures forecasting model. It can provide forecasts of the season-average price throughout the marketing year. In addition, the futures model can also be used to forecast the annual counter-cyclical payment rate for corn, soybeans, and wheat and it can be used to provide information on the likelihood of triggering marketing loan benefits. Forecasting the season-average price and CCP rate is important for policy analysis and budgetary planning purposes, providing USDA with valuable information to avoid exceeding the WTO ceiling on domestic support spending, as mandated by the 2002 Farm Act (Hoffman 2005 and USDA c).

Earlier attempts to evaluate the forecast performance of this model focused mainly on the standard accuracy measures of forecast performance, such as the mean absolute percentage error (Hoffman 2004; Hoffman 2001; Dohlman et al. 2000; Hoffman and Balagatas 2000; Hoffman 1992; Hoffman and Davison 1992; and Hoffman 1991). More rigorous tests are available to determine whether forecasts of the season-average price by the futures model meet the necessary conditions of futures market efficiency. Furthermore, would these forecasts gain in value if they encompassed the WASDE price projections as explained in Sanders and Manfredo 2005. Such evaluations could provide information to improve the futures models’ forecasts.

Objectives

Objectives of this paper include:

1. present the futures price forecast model for monthly forecasts of the U.S. season-average price received for corn, soybeans, and wheat
2. assess the performance of the futures forecast model including traditional forecast accuracy measures, such as, mean absolute error, mean absolute percentage error, and root mean squared percentage error from monthly season-average price forecasts, 1980 through 2005 crop years. Whether there is a statistical difference between the futures model forecast and WASDE projections is determined.
3. assess the futures model forecast, to determine whether it would benefit from encompassing WASDE price projections

Theoretical Framework

The efficient market hypothesis provides a conceptual framework for determining the forecast accuracy of futures markets. The futures price is an unbiased predictor of the cash price for a given delivery location and time period based on the efficient market hypothesis (Fama 1970 and 1991). According to the efficient market hypothesis, expert forecasts should contain no predictive information other than that contained in the futures market “forecast.” One common citation is that a necessary, but not sufficient, condition to reject futures market efficiency is that the alternative forecast models produce smaller mean squared forecast errors than futures-based forecasts. Also, if the futures model forecast provides the smallest mean squared error, then one cannot use the alternative forecast to generate trading profits.

This necessary condition has been tested in several grain and livestock markets with mixed results. Rausser and Just (1979) found that forecasts made by several commercial forecasting companies were generally not superior to the corresponding futures market prices. Rausser and Carter (1983) found futures market inefficiency in the soybean complex. Their results support the relative accuracy condition for futures market inefficiency for soybeans and soybean meal but the sufficient relative costs/benefits condition for inefficiency was not tested.

A review of pricing efficiency of agricultural futures markets by Garcia, Hudson, and Waller (1988) found mixed evidence regarding whether forecasting models can improve on the forecast performance of futures markets. The overall results of these studies are mixed depending on the markets examined and the alternative forecasting methods. The expectation is that forecasting studies will provide mixed evidence regarding market efficiency and trading profitability. However, whether consistent statistically significant results are found repeatedly for a given forecasting method is the real question.

Brandt (1985) suggested that forecasts by models or individuals can predict future price movements more accurately than the futures market and that producers and packers can gain from this information. Bessler and Brandt (1992) used vector autoregression of an expert's forecasts, the futures prices, and actual cash prices to show that cattle futures prices are not an efficient forecast of actual cash prices, while hog futures and the expert forecast are about equal. Irwin, Gerlow, and Liu (1992) found no significant difference between the forecast accuracy of live hog and live cattle futures prices compared to U.S. Department of Agriculture (USDA) expert predictions over a period of the first quarter of 1980 to the fourth quarter of 1991.

Kastens and Schroeder (1996) found that Kansas City July wheat futures from 1947 to 1995 outperformed econometric forecasting. Kastens, Jones, and Schroeder (1998) determined the forecast accuracy of five competing cash price forecasts over the 1987-96 period. Commodities examined were major grains, slaughter steers, slaughter hogs, feeder cattle, cull cows and sows. The traditional forecast method of deferred futures plus historical basis had the greatest accuracy. Adding complexity to forecasts, such as including regression models to capture nonlinear bases or biases in futures markets, did not improve accuracy.

Zulauf and Irwin (1997) cite that available evidence on individual-generated forecasts is largely consistent with an efficient market. Furthermore, they cite work by Patel, Neckhauser, and Hendricks (1991). "Market efficiency is expected when investors play for significant stakes, investors have sustained opportunities for practice, economic selection eliminates non-rational traders, and poaching (i.e. arbitrage) opportunities can be seized readily. These characteristics describe futures and options markets where entry is easy, trading opportunities exist daily, and losses are visible daily and are magnified through the leverage provided by margin money." (Zulauf and Irwin, 1997, p. 324).

Sanders and Manfredo (2005) advance the methodological procedures for testing futures market efficiency. They show that the necessary condition is not stringent enough to reject market efficiency. They demonstrate that to truly reject market efficiency, an alternative forecast must also encompass the information contained in other forecasts. They found that by applying this more stringent encompassing test, the necessary condition was satisfied to reject the null hypothesis of pricing efficiency.

Although assumptions for the futures forecasting model differ slightly from those of the efficient market hypothesis, it is assumed that these differences would not invalidate the use of this hypothesis. The futures price is combined with a basis forecast to generate a forecast of the cash price received at the U.S. level. Monthly cash price forecasts are derived from futures prices for each contract traded throughout the marketing year plus a monthly basis. This information captures market carries or inversions. Actual cash prices are used for the monthly price, as they become available. Each month's marketings are used as a weight to construct a season-average weighted price.

Given that futures prices contain useful cash price information, they must be converted into specific cash price forecasts. Many prior studies using futures prices have focused on a given location, a given grade, and one time period, such as harvest. Most market participants need to be able to forecast a price for a given location and time when they plan to buy or sell a commodity. Thus, they need to predict the basis, which is the difference between the local cash price and the specified futures price. In contrast, government policy and commodity analysts are interested in forecasting a commodity's season-average price, including within-year monthly price patterns. Intra-year price patterns provide information about an expected "normal" or "inverted" market.

Using futures prices to forecast a season-average price is slightly different than using a futures price to forecast a price for a given location, a given grade, and a specified time period. First, the monthly cash price received represents an aggregation of different grades of corn, soybeans, or wheat and thus is different from No. 2 yellow corn, No 2 yellow soybean, or No. 2 hard red winter wheat price at the local elevator. The futures model uses the futures price for a specific grade of corn, soybeans, or wheat, U.S. No. 2 yellow, to predict the season-average cash price received for U.S. producers. Secondly, the model does not focus on a given location but on an average for the U.S. The monthly cash price received represents an average U.S. price received by producers, in contrast for a specific location. The monthly cash price received represents a U.S. average and the basis represents an average for the U.S., not a specific location. The cash price received by U.S. producers is an aggregation of all grades of corn and is collected by the National Agricultural Statistics Service. A monthly national basis is computed (cash price received less futures price) and it is assumed that the difference in grades will be captured by the basis. Thirdly, the time period is expanded from one period, such as harvest, to the entire marketing year thus requiring five futures contracts instead of one contract.

Forecast Model

The futures forecasting model consists of several components: futures prices, farm prices received, basis values (farm price received less futures), and marketing weights. The season-average price-received forecast is derived from a summation of weighted forecasts of the producer price received for each month of the marketing year. These monthly forecasts are derived from the futures contracts traded throughout the marketing year. For each marketing year month, the forecast begins with the nearby futures contract price except when the contract expires in that month, in which case the next nearby contract is used. Next, the monthly futures price is adjusted by a basis (derived from a 5-year moving average farm price less a 5-year moving average futures price) to compute the U.S. monthly farm price forecast. These monthly farm price forecasts are then weighted based on monthly marketing volumes reported by USDA.

Thus, the forecast of the season-average corn price received is derived from 12 monthly farm price forecasts, which in turn are based on five futures contracts traded throughout the marketing year. The forecast period for each marketing year covers 16 months for corn and soybeans beginning in May which is 4 months before the start of the marketing year. The forecast period for wheat covers 13 months and begins 1 month before the start of the marketing year. The forecast period concludes with August for corn and soybeans, the last month of their marketing year, and concludes with May for wheat, the last month of its marketing year. The forecasts are made monthly to coincide with the release of USDA's WASDE projections.

The season-average forecast is initially based on futures prices, but these prices are replaced with the actual monthly average price received by farmers, as they become available from USDA's National Agricultural Statistics Service. A midmonth farm price received for September (corn and soybeans) or June (wheat), the first month of the marketing year, becomes available in late September or late June. Consequently, the season-average price forecast becomes a composite of futures forecasts and farm prices received beginning with the October forecast for corn and soybeans, the 6th month of the 16-month forecasting period. This composite price forecast begins with the July forecast for wheat, the 3rd month of the 13-month forecasting period.

Example forecast periods

<u>Futures-derived forecasts</u>--Forecasts of the corn and soybean season-average price received during May through September (May through June for wheat) use only futures-derived forecasts of the monthly price received (table 1).

<u>Composite of actual prices received and a futures-derived forecast of the monthly price received</u>--Forecasts of the season-average price received during October through August for corn and soybeans (July through May for wheat) use a combination of actual monthly prices received and a futures-derived forecast of the monthly price received. Forecasts during the month of January include 4 months of actual prices received and 8 months of futures-derived forecasts for corn and soybeans; 7 months of actual prices received and 5 months of futures-derived forecasts for wheat (table 1).

Mathematical Models

The **corn** or **soybean** forecast model of the season-average farm price (SAP) for any crop year is computed as follows: [2]

$$
\text{(1)}\quad SAP_m = \begin{cases} \sum_{i=1}^{12} W_i\,(F_{i,m} + B_i) & \text{for } m = \text{-3 to 1.} \\ \sum_{i=1}^{m-1} W_i\, P_i + \sum_{i=m}^{12} W_i\,(F_{i,m} + B_i) & \text{for } m = \text{2 to 12.} \end{cases}
$$

The forecast of the season-average farm price received made in month *m* is equal to SAP_{m}. The marketing weight (percent) for marketing year month *i* is equal to W_i. The farm price received in marketing year month *i* is equal to P_i. The observed monthly futures price in month *m* for the nearby futures contract of month *i* is equal to $F_{i,m}$. The expected basis, B_i, is equal to farm price received in month *i*, minus average futures price in month *i* for the nearby futures contract. [3] This basis is usually a negative number. The crop year has 12 months (*i*), September through August, *i* = 1, 2, 3, …,12. The season-average price forecasts are made monthly (*m*), *m* = -3, -2, -1, 0, 1, 2, 3, ... ,12, May through August; in September *m* = *i*.

The **wheat** forecast model of the season-average farm price (SAP) for any crop year is computed as follows: [4]

$$
\text{(2)}\quad SAP_m = \begin{cases} \sum_{i=1}^{12} W_i\,(F_{i,m} + B_i) & \text{for } m = \text{0 to 1.} \\ \sum_{i=1}^{m-1} W_i\, P_i + \sum_{i=m}^{12} W_i\,(F_{i,m} + B_i) & \text{for } m = \text{2 to 12.} \end{cases}
$$

The crop year has 12 months (*i*), June through May, *i* = 1, 2, 3, …,12. The season-average price forecasts are made monthly (*m*), *m* = 0, 1, 2, 3, ... ,12, May through August; in May *m* = *i*. All other variables are defined under the corn and soybean model.

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[2] The first expression in equation 1 refers to futures derived forecasts of the season-average price, and the second expression of equation 1 refers to the composite of actual and futures derived forecasts of the season-average price.
[3] The nearby futures price is always used except when the forecast month coincides with the closing month of the nearby futures contract. For this situation, the next nearby futures contract is selected.

Futures Prices

Five corn and five wheat futures contracts are used for each of their models. These contracts close in the months of December, March, May, July, and September. Corn uses the #2 yellow corn futures contract traded on the Chicago Board of Trade and wheat uses the # 1 hard red wheat contract traded on the Kansas City Board of Trade. The soybean futures model uses seven # 2 yellow soybean futures contracts traded on the Chicago Board of Trade with each of the contracts closing in the months of November, January, March, May, July, August, and September.

Farm Price Received

The monthly price received by U.S. producers is updated by the National Agricultural Statistics Service (NASS). Through sampling, NASS collects sales from producers to first buyers. The price is determined by dividing sales by quantity sold. This price represents all grades and qualities. These prices are reported monthly and also annually. The monthly quantity sold, expressed as a percent of total marketing year quantity sold, is used in the model to compute a monthly price weight.

Basis

The basis used in this model is equal to the farm price received less the futures price. The basis is computed as a 5-year moving average of the monthly U.S. price received by producers less a monthly average of the nearby futures closing price observed for the particular month. For example, the September basis for corn is a 5-year moving average of the difference between the September average cash price received by producers and September's average closing price of the nearby December futures contract. This basis calculation reflects a composite of basis-influencing factors because it represents an average of U.S. conditions, rather than a specific geographic location. [5] Also since the cash price received consists of different quality levels but

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[4] Equation 1 refers to futures derived forecasts of the season-average price, and equation 2 refers to the composite of actual and futures derived forecasts of the season-average price.

[5] Several factors affect the basis and help explain why the basis varies from one location to another. Some of these factors include: local supply and demand conditions for the commodity and its substitutes, transportation and

the futures price is for No. 2 yellow corn, No. 2 yellow soybeans, or No. 2 hard red winter wheat, the basis could vary differently (perhaps more) than when computing a basis for a specific grade level. A 5-year moving average of these monthly bases is computed and updated annually.

Marketing Weights

Monthly crop marketings are used to construct a weighted season-average price. Each month's weight represents the proportion of the marketing year's crop marketed in that month, expressed as a percentage. A 5-year moving average of these monthly weights is computed and updated annually. The monthly marketing weights are used to compute a price weight for each month. The monthly price weight is equal to the monthly farm price received multiplied by the monthly marketing weight.

Data

The futures forecasting model requires monthly data by marketing year for the following items: 1) monthly average closing prices from the nearby futures contracts, 2) monthly (mid- and full-month) farm price received, 3) monthly marketing weights, and 4) monthly futures closing prices (day of WASDE release) from the nearby futures contracts. [6] These data are collected for marketing years 1975 through 2005 and are used to construct the 5-year moving average basis and marketing weights. The 5-year averages for monthly basis values and marketing weights begin with 1975-79 data and are updated to the present. A monthly futures forecast requires an update of monthly futures prices, available cash prices, and marketing weights on a periodic basis.

Historical daily closing prices by contract for corn (December, March, May, July, and September) and for soybeans (November, January, March, May, July, August, and September)

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handling charges, transportation bottlenecks, availability and costs of storage, drying capacities, grain quality, and market expectations.

[6] WASDE release times went from 3:30 pm to an 8:30 am release as of May 1994. Thus, initially the WASDE release date used is the day after the release but with the change in release times, the WASDE release date used became the day of release.

are obtained from the Chicago Board of Trade for marketing years 1975 through 2005. Prices received by producers are obtained from *Agricultural Prices*, published by USDA's National Agricultural Statistics Service (USDA 1975-2006a). Marketing weights by month for 1975 through 1976 marketing years are published in the 1977 December issue of *Crop Production* (USDA, 1975-1996b). The marketing weights for the remaining marketing years, 1977 through 2005, are published in the various annual summaries of *Agricultural Prices.* For comparison to the futures model price forecasts, price projections from the U.S. Department of Agriculture are obtained from *World Agricultural Supply and Demand Estimates* (WASDE) published by USDA’s World Agricultural Outlook Board (USDA 1980-2006d).

Forecast Performance and Futures Market Efficiency

The forecast performance of the futures model forecast is first evaluated using traditional forecast accuracy measures. The standard necessary condition to reject futures market efficiency is that a competing forecast provides a smaller mean squared error than the futures market forecast. If the futures model forecast does not have the smallest mean squared forecast error, the futures model forecasts may satisfy the necessary condition to reject efficiency. However, it is important to determine whether the WASDE projections generate statistically smaller projection errors.

The modified Diebold and Mariano (MDM) test is used to test for statistical differences between futures model forecasts and a competing forecast, WASDE price projections (Harvey, Leybourne, and Newbold, 1997). Although significant advances have been made in evaluating the statistical difference in prediction errors by stating the necessary condition in a mean squared error framework may be misleading (Sanders and Manfredo). Conditional efficiency is not met if a given forecast has a mean squared error that is smaller than a competing forecast, but the given forecast may not “encompass” all the information in the competing forecast. In this case, a trader could add his forecast to that of the futures market to obtain a superior overall prediction, and potentially use it to extract trading profits from the futures market. Thus, the efficient futures model forecast must do more than produce the smallest mean squared forecast error, it must encompass all competing forecasts. This stricter test of pricing efficiency, forecast encompassing, is tested in an encompassing framework also using the modified Diebold and Mariano (MDM) test (Harvey, Leybourne, and Newbold, 1998).

Procedures

In determining the necessary conditions for the market efficiency tests, the futures model forecast is the selected forecast and the mid-point of the WASDE price projections is the alternative or competing forecast. Futures model forecast performance for corn, soybeans, and wheat are first evaluated using the traditional forecast accuracy measures for the marketing years 1980 through 2005. Forecast accuracy measures analyzed include:

mean error (3) $= 1/n\sum_{t=1}^{n} E_t$

mean absolute error (MAE) (4) $= 1/n\sum_{t=1}^{n} |E_t|$

mean absolute percentage error (MAPE) (5) $= 1/n\sum_{t=1}^{n} \left| \left((A_t - F_t)/A_t \right) \right| \times 100$

mean squared error (MSE) (6) $= 1/n\sum_{t=1}^{n} E_t^2$

root mean squared percentage error (RMSPE) (7) $= \left[\left(\sqrt{1/n\sum_{t=1}^{n} E^2} \right) / \left(1/n\sum_{t=1}^{n} A_t \right) \right] x100$

The error provides information on a positive or negative deviation from the actual price but the mean error may be small, as the positive and negative errors tend to offset each other. The absolute error removes this problem by taking the absolute value of each error. The absolute percentage error provides still more information than the prior two measures because it relates the error to the actual price. The mean squared error has the advantage of being easier to handle mathematically and is often used in statistical optimization. The root mean squared percentage error is the most common measure of forecast accuracy.

An alternative forecast, World Agricultural Supply and Demand Estimates (WASDE), is published monthly in USDA's *World Agricultural Supply and Demand Estimates* report. The WASDE projection represents a composite projection from analysts' judgment supplemented with econometric model forecasts, futures prices, and monthly cash prices. The comparisons of the futures model forecasts to the WASDE projections (mid-point of the range) are computed monthly. The monthly futures forecasts are computed from closing futures prices on the day of WASDE release.

Statistical test for difference between the futures model forecasts and WASDE projections

The test statistic used to determine whether the errors from two forecast methods are statistically significant is the Modified Diebold-Mariano test (MDM) proposed by (Harvey, Leybourne, and Newbold (1997). This test involves specifying a cost-of-error function, g(e) = squared error, of the forecast errors e and testing pair-wise the null hypothesis of expected equality of forecast performance. Harvey, Leybourne, and Newbold (1997) argue that critical values from the Student's t distribution with (n-1) degrees of freedom should be computed for the two different forecast methods. The test statistic is

(8) $$\text{MDM} = \left[\frac{n+1-2h+n^{-1}h(h-1)}{n}\right]^{1/2} \times \left[n^{-1}\left(\hat{\gamma}_0 + 2\sum_{k=1}^{h-1}\hat{\gamma}_k\right)\right]^{-1/2}\bar{d}$$

where: $\hat{\gamma}_k = n^{-1}\sum_{t=k+1}^{n}(d_t - \bar{d})(d_{t-k} - \bar{d})$ is the estimated *k*th autocovariance of d_t and $\bar{d}$ is the sample mean of d_t. This statistic is computed for one-step ahead forecasts where h = 1 and $d_t = g(e_{1t}) - g(e_{2t})$, $\bar{d}$ is the average difference across all forecasts. The null hypothesis is $E[g(e_{1t}) - g(e_{2t})] = 0$ and the alternative hypothesis is $E[g(e_{1t}) - g(e_{2t})] \neq 0$; t = 1, …, n, where n = 26. Since h = 1 equation (8) becomes

(9) $$\text{MDM} = [(n-1)]^{1/2} \text{ x} \left[1/n\left(\sum_{t=1}^{n}\left(d_t - \bar{d}\right)^2\right)\right]^{-1/2}\bar{d}$$

Specific definitions for the MDM test applied to the futures model forecasts and WASDE projections are given next. When testing the significant differences of the squared errors of the futures forecasts and the WASDE projections, $g(e_{ft}) = e^2_{ft}$ is the squared error for the futures forecasts for the day of release of WASDE and $g(e_{wt}) = e^2_{wt}$ is the squared error for the WASDE price projections. The difference between the squared errors of the futures model forecast and WASDE projections at time t is $d_t = e_{ft} – e_{wt}$. The average difference across these forecasts, crop years 1991-2005, is $\bar{d}_m$ for each forecast month (*m*), May through August, $m = -3, -2, -1, 0, 1, 2, 3, ... ,12$ for corn and soybeans, and May through May, $m = 0, 1, 2, 3, \dots 12$ for wheat. The MDM test statistic for the futures model forecasts and WASDE projections is referred to as MDM_m for each forecast month (*m*). The null hypothesis is $E[g(e_{ft}) – g(e_{wt})] = 0$ and the alternative hypothesis is $E[g(e_{ft}) – g(e_{wt})] \neq 0$, $t = 1, \dots, n$, where $n = 26$.

Advantages of the MDM test are that it is insensitive to contemporaneous correlation between the forecast errors and its power declines only slightly with departures from normality as demonstrated by Harvey, Leybourne, and Newbold (1997). These characteristics are important because sometimes one tries to differentiate between forecasts that are correlated and possess occasional large errors. Further advantages of the MDM test include its applicability to multiple-step ahead forecast horizons, its non-reliance on the assumption of forecast unbiasedness, and its applicability to cost-of-error functions in addition to the conventional quadratic loss. Harvey, Leybourne, and Newbold (1997) argue that the MDM statistic is the best available method for determining the significance of observed differences in competing forecasts.

Statistical test for forecast encompassing

As mentioned previously, Sanders and Manfredo (2005, p. 612) advance the methodological procedures for testing futures market efficiency. They state that while it is possible for a forecast to have a mean squared error smaller than a competitor, it is not conditionally efficient if the forecast does not “encompass” all the information in the competing forecast. They show that pricing efficiency in the futures market assumes that information is used efficiently and there is no risk premium and that the returns for holding a futures contract from time $t - n$ to time $t(f_t – f_{t-n})$ is uncorrelated with the available information set at $t – n(\Omega_{t-n})$. They demonstrate that to truly reject market efficiency, a competing forecast must also encompass the information contained in other forecasts. Harvey, Leybourne, and Newbold's 1998 test for forecast encompassing is expressed in the following equation:

(10) $e_{ft} = \alpha + \lambda (e_{ft} - e_{wt}) + e_t$

Where e_{ft} is the forecast error series of the futures model forecast and e_{wt} is the forecast error series of the alternative forecast, WASDE price projections. Both e_{ft} and e_{wt} are expressed in their raw error values, in contrast to absolute values or squared error values. A test of the null hypothesis, $\lambda = 0$, in the above equation is a test that the covariance between e_{ft} and $(e_{ft} - e_{wt})$ is zero. A failure to reject the null hypothesis means that a composite forecast (combining the futures model forecasts and WASDE projections) cannot be constructed from the two series that would result in a smaller expected squared error than using the preferred or futures model forecast. Thus, the futures model forecast is said to be "conditionally efficient" or to "encompass" the competing forecast. However, rejection of the null hypothesis allows us to infer that the futures model forecast does not contain the marginal information of the competing WASDE price projection.

Traditional regression-based tests of forecast encompassing in equations often have size and power problems in small samples or when forecast errors are nonnormal (Harvey, Leybourne, and Newbold, 1998). Harvey, Leybourne, and Newbold (1998) also devised a test for use in forecast encompassing. They extend the MDM test to examine pairwise tests of forecast encompassing by defining $d_t = e_{ft}(e_{ft} - e_{wt})$ and $\bar{d}$ as the sample mean of d_t, where e_{ft} and e_{wt} are defined as in equation (10). In this case the MDM test is simply testing for a zero covariance between e_{ft} and $(e_{ft} - e_{wt})$, or that $\lambda = 0$ in equation (10).

Results

Descriptive statistics for the two forecast method's error series are first presented. Next, traditional measures of forecast accuracy are presented followed by tests to determine whether the two forecasts are statistically significant. Lastly, tests are presented determining whether the futures model forecast would benefit from encompassing the alternative forecast, WASDE price projections.

DescriptiveStatistics

Basic statistics for both forecast methods are found in table 2. These statistics include the mean error, standard deviation, range, and mean percent error. The variance, as measured by the standard deviation or range, of either forecast method (futures model or WASDE projections) tends to decline throughout each successive forecast period as expected. The mean error provides information on whether the errors are over or under shooting especially when compared to the absolute error. For each forecast method and for each commodity, the mean error had a small positive or negative value after the initial forecast periods of the forecast cycle, indicating that many of the errors tended to offset each other over a period of 26 years. However, in the early forecast periods for each forecast method and each commodity, WASDE projections appear have a lower mean percent error than the futures model forecasts (see figures 1 and 2). This suggests a larger risk premium for the futures model forecasts than for WASDE projections in the early months of the forecast cycle. For the remaining forecast periods the mean percent error tends to become more equal for each of the two forecast methods.

Traditional Forecast Accuracy Measures

Forecast accuracy measures are examined for corn, soybeans and wheat for each of the forecast periods, crop years 1980 through 2005 (table 3). The forecast accuracy discussion focuses on two forecast accuracy measures; the mean absolute percentage error (MAPE) and root mean squared percent error (RMSPE).

As expected, the mean absolute percentage error and root mean squared percentage error decline for corn, soybeans, and wheat throughout the forecast cycle (May through August for corn and soybeans and May through May for wheat) for both the futures model forecasts and the WASDE projections. While the percentage error for each of these accuracy measures differs slightly by forecast period, both reinforce the general findings regarding the size of the error. The general decline in these forecast errors occurs because of the additional information that becomes available for each commodity throughout the forecast periods. While the rate of decline in the mean absolute percentage error or root mean squared percentage error is similar for corn and soybeans it is somewhat different for wheat because of the difference in months within wheat's marketing year relative to corn and soybeans and the corresponding market information. The errors are greater for wheat than corn or soybeans during the first month of the marketing year because it takes longer for wheat to establish its final production since it must cover both the winter and spring harvest periods which extends from May to September. Furthermore, the magnitude of the soybean error, regardless accuracy measure or forecast method, in many forecast periods appears to be about 1-percentage point less than for corn. This could be due to soybean's monthly crush report which provides a more predictable domestic soybean disappearance than corn's reliance upon the quarterly stocks report to compute domestic disappearance.

By focusing on the decline in corn's MAPE or RMSPE one can illustrate the effect information has on the error. For example, the mean absolute percentage error for 1980-2005 for both forecast methods declined by 1 to 2 percentage points between the second and third forecast months (June and July), reflecting, in part, new crop information such as the June acreage report and crop progress. The MAPE or RMSPE dropped another 2 to 5 percentage points between July and August, reflecting, in part, information on the new crop's estimated yield and crop progress. The difference between the August and September is less pronounced.

The difference between the September and October forecasts represents a 1 to 2 percentage point decline in the MAPE or RMSPE. This difference reflects, in part, information from the grain stock report (beginning inventories to start the new crop year), production information on the new crop, and an estimate of the mid-month cash price received for September. Remember that forecasts from May through September rely on all futures prices for the monthly price forecasts but the October forecast uses a mid-month September initial actual farm price plus futures price for the eleven remaining months.

The decline in the MAPE and RMSPE percentage errors begins to slow with October. The percentage error declines by 1 percentage point per month between October and November, November and December, and December and January, reflecting additional information on production, additional cash price estimates for each month, and the grain stocks report for January. Additional use information, such as monthly exports, becomes available from the Census Bureau approximately two months after the month observed.

Furthermore, the rate of decline continues to slow between January and July as the average forecast error declines a total of about 2 percentage points over this six-month period. This period reflects additional cash prices, the grain stock reports, and additional use information. The July futures forecast of the season-average price consists of a futures forecast for July and August prices and cash prices for the previous 10 months. The remaining month, August, reflects about a 1-percentage point error. The August futures forecast includes a futures forecast for the August price and 11 cash prices for the previous months.

Potential sources of error for the futures model forecast are the 5-year average basis value or the 5-year average marketing weights. In some years the basis is far different than the 5 year average. This is especially true in years of rising futures prices or years of declining futures prices. Preliminary work suggests that improving the basis forecast has more potential to improve the season average price forecast than improving the marketing weight forecast (Hoffman and Balagatas).

Futures Model Forecast Efficiency

The standard necessary condition to reject futures market efficiency is that an alternative forecast provides a smaller mean squared error than the futures market forecast. If the futures model forecast does not have the smallest mean squared forecast error, the futures model forecasts may satisfy the necessary condition to reject efficiency.

Since the futures model does not have the smallest mean squared errors in 9 of the 16 forecast periods for corn, 3 of the 16 forecast periods for soybeans, and 11 of 13 forecast periods for wheat, the futures model forecast may satisfy the necessary condition to reject the null hypothesis of market efficiency during these periods (table 3). However, a statistical test is necessary to determine whether the alternative forecast, WASDE price projections, generates statistically smaller prediction errors.

Furthermore, the futures model forecasts possess a smaller mean squared error than the alternative forecast, WASDE price projections, in 7 out of 16 forecast periods for corn (October through February, June, and August), 13 out of 16 forecast periods for soybeans (June, August through March, and June through August), and 2 out of 13 forecast periods for wheat (December)(table 3). [7] [8] Again, a statistical test is necessary to determine whether the futures model forecast generates statistically smaller prediction errors than the WASDE price projections.

The MDM test as found in equation (9) is used to test the statistical difference in mean squared error from both forecasting methods for each of the 16 forecast periods for corn and soybeans and for each of the 13 forecast periods for wheat. The null hypothesis states that the squared errors from either distribution are equal. Therefore, we must reject the null hypothesis to find statistical differences in the forecasts. The critical values of t are 2.78 and 2.06, respectively, using a 1-percent or 5-percent significance level and a t distribution with (n-1) degrees of freedom. The modified Diebold-Mariano test statistics for corn, soybeans, and wheat are shown in table 4. Since the MDM test statistics are smaller than the critical t value of 2.06 for most of the forecast periods, we cannot reject the null hypothesis which states that the forecasts errors of the two forecast methods are equal to zero. [9] The $d_t = (e_{ft} – e_{wt})$ are shown in figure 2a, 2b, and 2c for the May forecast period only.

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[7] Results between forecast methods are nearly identical for either the mean absolute percentage error or the root mean squared percentage error

[8] The wheat futures model uses futures price information from the Kansas City Board of Trade's hard red winter wheat contract. However, other contracts exist for soft red winter and hard red spring wheat, but since hard red winter wheat comprises most of the wheat production volume it was chosen to represent the all wheat price. In contrast the WADE projections may have better information concerning all classes of wheat which may explain why the WASDE projections had lower squared errors than the futures model forecasts in 11 out of 13 forecast periods.

[9] Two exceptions were the December and January soybean forecast periods.

Thus, these findings support the efficiency of the futures model forecasts. The MDM test could not distinguish a statistical difference between the accuracy of the two different forecasts for most forecast periods (table 4). Although for some forecast periods the futures model forecasts had smaller mean squared errors than did the WASDE projections, for other forecast periods the mean squared errors for the WASDE projections were smaller than the futures model forecast. So in general by applying the traditional necessary condition, forecast efficiency is not rejected because the WASDE projections do not produce statistically smaller errors. However, as Sanders and Manfredo (2005) caution this conclusion may be misleading if the futures forecast does not encompass all the information in the alternative WASDE projections.

Forecast Encompassing Test

Forecast encompassing is tested for each commodity and for each forecast period (table 5). The null hypothesis states that the futures model forecast encompasses the information contained in the WASDE price projections.

The null hypothesis is rejected at either the 1-percent or 5-percent level for 11 of 15 forecast periods for corn, 2 of 16 periods for soybeans, and 7 of 13 forecast periods for wheat (table 5). The critical t value is 2.78 and 2.06, based on a 1-percent and 5 percent significance level, respectively, and a t distribution with (n-1) degrees of freedom. The $d_t = e_{ft} (e_{ft} – e_{wt})$ are shown in figure 2a, 2b, and 2c for the May forecast period only. Thus encompassing necessary condition for market inefficiency is met for the above stated forecast periods (table 5). These results are consistent with WASDE projections having a smaller mean squared error for many of the forecast periods that rejected the null hypothesis.

A failure to reject the null hypothesis implies that a composite forecast cannot be constructed from the two forecast error series that would result in a smaller expected squared error than using the futures model forecast. Such a situation is referred to as being “conditionally efficient” or to “encompass” the WASDE projections. Several forecast periods could not reject the null hypothesis: 5 of the 16 corn forecast periods, 14 of the 16 forecast periods for soybeans, and 6 of 13 forecast periods for wheat (table 5). These results are consistent with the futures model forecasts having a smaller mean squared error for many of the forecast periods that could not reject the null hypothesis, although this was less the case for wheat than either corn or soybeans.

Harvey and Newbold (2000) state that a failure to reject the null hypothesis may not necessarily mean that the futures model forecasts are strictly dominant to the WASDE projections. Two reasons cited for this situation are that forecasts may be highly correlated which means they cannot produce a smaller mean squared error relative to an individual forecast or there may be large sample variability. As stated previously, this encompassing test provides much stronger statistical evidence than the test for differences in mean squared errors.

Summary and Conclusions

A futures forecast model was presented that provided season-average price forecasts. These futures model forecasts had mean squared errors or root mean squared percentage errors that were less than the WASDE projections, but not in all forecast periods. The modified Diebold Mariano statistical test was conducted to determine whether the squared errors from the two different forecast methods were statistically different from zero. In all forecast periods for all commodities, except two for soybeans, forecast errors from the two forecasting methods were found to be not statistically different. Thus the standard necessary condition to reject market efficiency was not met. If we rely upon this test, we would conclude that in general the futures model forecasts are efficient. However, this method could lead to incorrect conclusions.

A more stringent test, forecast encompassing, was conducted. Instead of general support for the futures model's forecast efficiency, we found that the futures model forecasts were "conditionally efficient" for several but not all forecast periods. A failure to reject the null hypothesis implies that a composite forecast cannot be constructed from the two forecast error series that would result in a smaller expected squared error than using the futures model forecast. This condition is referred to as "conditionally efficient" or to "encompass" the WASDE projections. The null hypothesis could not be rejected in 5 of the 16 corn forecast periods, 14 of 16 forecast periods, and 6 of 13 forecast periods for wheat.

The futures model forecasts did not contain all the information in the competing WASDE price projections for some of the forecast periods. With this information the necessary condition to reject the null hypothesis of futures model forecast efficiency was satisfied for 11 of 16 forecast periods for corn, 2 of 16 forecast periods for soybeans, and 7 of 13 forecast periods for wheat. This suggests that the combination of the two forecast methods would provide a better forecast during these periods than the futures model forecasts. Although the necessary condition is met for these forecast periods, an examination of the sufficient condition is needed to make further definitive statements regarding market efficiency.

Inefficiencies found in the futures model forecasts could possibly be reduced with more accurate forecasts of the basis or marketing weights. Futures forecasts were derived from a 5-year moving average of both the basis and marketing weights.

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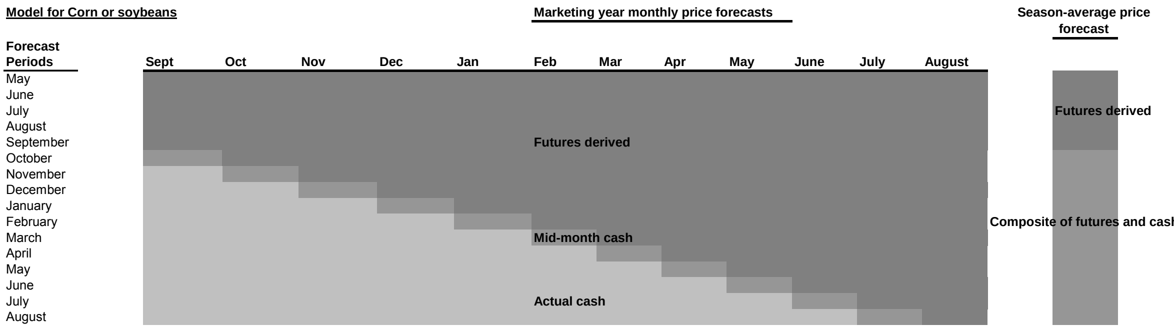
Table 1. Futures Model's Forecast Periods and Derivation of Monthly and Season-Average Price Forecast



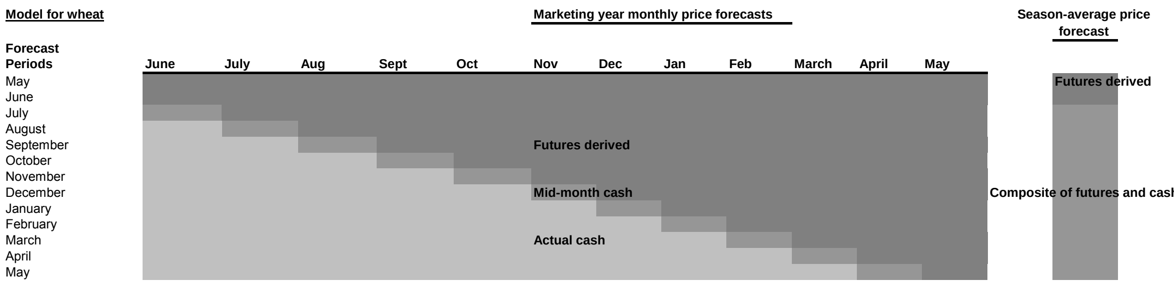


Table 2. Raw Error Statistics for the Futures Model Forecasts and WASDE Projections of the Season-Average Price Received for Corn, Soybeans, and Wheat, crop years 1980 through 2005.

Commodity and Forecast Periods	Futures						WASDE					
	Mean	Standard Deviation	Range: Minimum	Range: Maxiumum	range	Mean Percent Error	Mean	Standard Deviation	Range: Minimum	Range: Maxiumum	range	Mean Percent Error
	Dollars per bushel					Percent	Dollars per bushel					Percent
Corn												
May	0.16	0.40	-0.64	1.02	1.66	8.52	-0.06	0.38	-0.74	0.69	1.43	-1.05
June	0.13	0.38	-0.71	0.94	1.65	7.24	-0.03	0.38	-0.72	0.69	1.41	-0.12
July	0.10	0.38	-0.55	1.01	1.56	4.89	0.01	0.33	-0.49	0.75	1.24	1.24
August	0.05	0.27	-0.56	0.60	1.16	2.68	0.05	0.26	-0.59	0.64	1.23	2.69
September	0.03	0.24	-0.45	0.48	0.92	1.42	0.06	0.23	-0.49	0.49	0.98	2.47
October	0.01	0.19	-0.48	0.34	0.82	0.50	0.03	0.20	-0.32	0.39	0.71	1.35
November	0.01	0.16	-0.42	0.39	0.81	0.65	0.01	0.19	-0.32	0.44	0.76	0.08
December	-0.02	0.12	-0.37	0.20	0.57	-0.64	0.00	0.16	-0.30	0.44	0.74	-0.27
January	0.00	0.12	-0.26	0.28	0.54	0.19	0.01	0.12	-0.25	0.32	0.57	0.37
February	0.01	0.10	-0.19	0.21	0.40	0.48	0.01	0.11	-0.19	0.32	0.51	0.36
March	0.01	0.09	-0.16	0.17	0.33	0.71	0.01	0.08	-0.19	0.17	0.36	0.41
April	0.03	0.07	-0.12	0.19	0.30	1.25	0.02	0.07	-0.19	0.15	0.34	0.77
May	0.02	0.07	-0.14	0.15	0.28	0.95	0.02	0.06	-0.19	0.12	0.31	0.75
June	0.02	0.05	-0.08	0.10	0.18	0.80	0.02	0.05	-0.14	0.12	0.26	0.71
July	0.01	0.04	-0.05	0.10	0.16	0.52	0.01	0.04	-0.06	0.12	0.18	0.49
August	0.00	0.03	-0.06	0.09	0.15	0.17	0.01	0.03	-0.04	0.12	0.16	0.47
Soybeans												
May	0.23	0.93	-1.91	1.84	3.75	5.17	-0.19	0.91	-2.39	1.93	4.32	-2.27
June	0.16	0.87	-1.89	1.60	3.49	3.68	-0.18	0.90	-2.39	1.93	4.32	-2.07
July	0.13	0.83	-2.21	1.64	3.85	2.69	-0.14	0.79	-2.49	1.43	3.92	-1.59
August	0.02	0.63	-2.05	0.91	2.96	0.51	-0.02	0.66	-2.29	1.08	3.37	0.06
September	0.10	0.55	-1.48	1.29	2.77	1.72	0.08	0.59	-1.64	1.17	2.81	1.40
October	0.02	0.46	-0.67	0.93	1.60	0.25	0.03	0.51	-0.88	1.17	2.05	0.43
November	0.02	0.36	-0.58	1.05	1.64	0.16	0.01	0.49	-0.85	1.17	2.02	-0.05
December	-0.03	0.22	-0.47	0.49	0.96	-0.40	0.02	0.39	-0.79	1.00	1.79	0.20
January	-0.02	0.16	-0.37	0.32	0.69	-0.34	-0.01	0.26	-0.64	0.42	1.06	-0.16
February	-0.05	0.15	-0.42	0.19	0.60	-0.85	-0.02	0.20	-0.49	0.28	0.77	-0.38
March	-0.01	0.12	-0.28	0.23	0.50	-0.19	-0.05	0.15	-0.49	0.15	0.64	-0.88
April	0.02	0.11	-0.11	0.45	0.56	0.29	-0.03	0.11	-0.34	0.26	0.60	-0.54
May	0.04	0.09	-0.15	0.34	0.49	0.54	-0.01	0.09	-0.14	0.31	0.45	-0.20
June	0.02	0.08	-0.20	0.20	0.40	0.41	0.00	0.09	-0.16	0.31	0.47	-0.06
July	0.02	0.08	-0.16	0.22	0.38	0.39	0.01	0.09	-0.14	0.32	0.46	0.15
August	0.02	0.06	-0.12	0.19	0.30	0.31	0.01	0.07	-0.14	0.27	0.41	0.24
Wheat												
May	0.11	0.59	-1.06	1.74	2.79	4.15	0.00	0.45	-1.10	0.70	1.80	0.51
June	0.04	0.45	-0.86	1.04	1.90	1.62	0.00	0.41	-1.00	0.70	1.70	0.42
July	-0.04	0.32	-0.53	0.69	1.22	-1.15	-0.05	0.31	-0.70	0.39	1.09	-1.47
August	-0.02	0.25	-0.47	0.45	0.92	-0.60	-0.03	0.25	-0.70	0.35	1.05	-1.24
September	-0.01	0.19	-0.43	0.30	0.73	-0.04	-0.03	0.18	-0.50	0.31	0.81	-1.18
October	0.01	0.17	-0.32	0.39	0.71	0.80	-0.01	0.14	-0.36	0.26	0.62	-0.49
November	0.01	0.13	-0.24	0.33	0.56	0.50	0.00	0.12	-0.29	0.24	0.53	-0.12
December	-0.01	0.07	-0.15	0.13	0.27	-0.27	0.01	0.10	-0.20	0.24	0.44	0.05
January	0.00	0.08	-0.14	0.14	0.28	0.26	0.01	0.07	-0.15	0.13	0.28	0.34
February	0.00	0.06	-0.13	0.11	0.23	0.25	0.01	0.05	-0.10	0.13	0.23	0.40
March	0.00	0.05	-0.12	0.09	0.21	0.13	0.00	0.04	-0.10	0.07	0.17	0.13
April	0.00	0.04	-0.11	0.11	0.22	0.02	0.00	0.03	-0.08	0.05	0.13	0.04
May	0.01	0.04	-0.08	0.10	0.18	0.20	0.01	0.03	-0.06	0.08	0.14	0.18

Figure 1a. Comparison of Forecast Percent Error for Corn; May Forecast Period

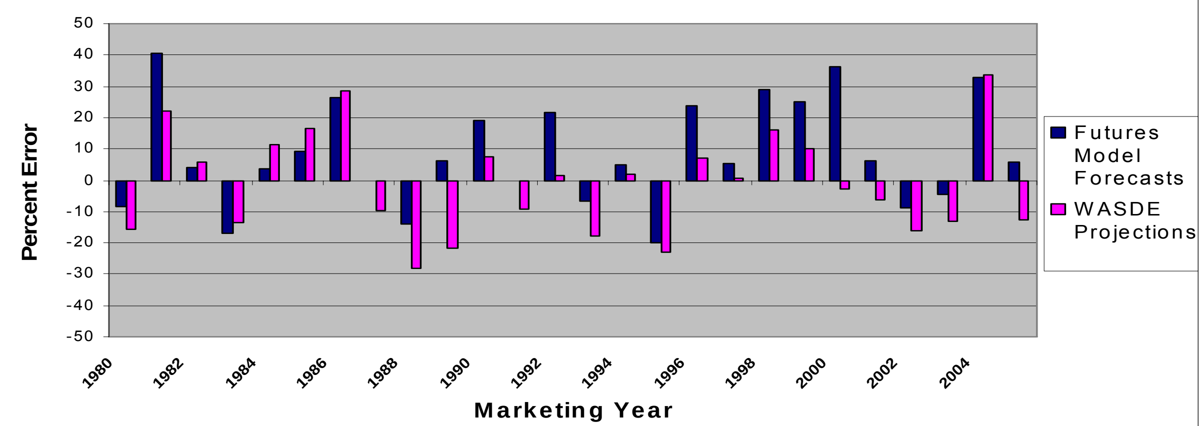


Figure 1b. Comparison of Forecast Percent Error for Soybeans; May Forecast Period

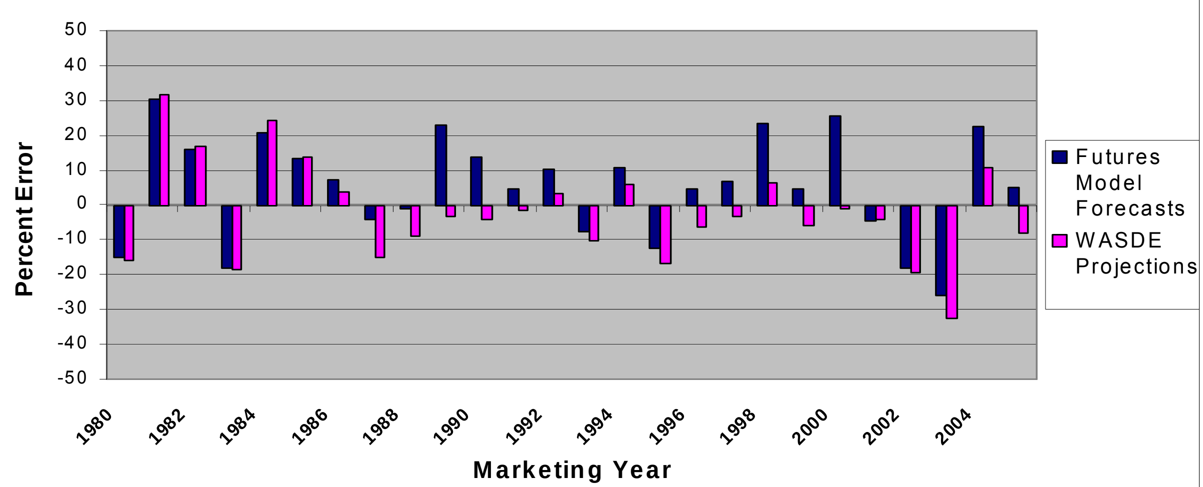


Figure 1c. Compaprison of Forecast Percent Error for Wheat; May Forecast Period

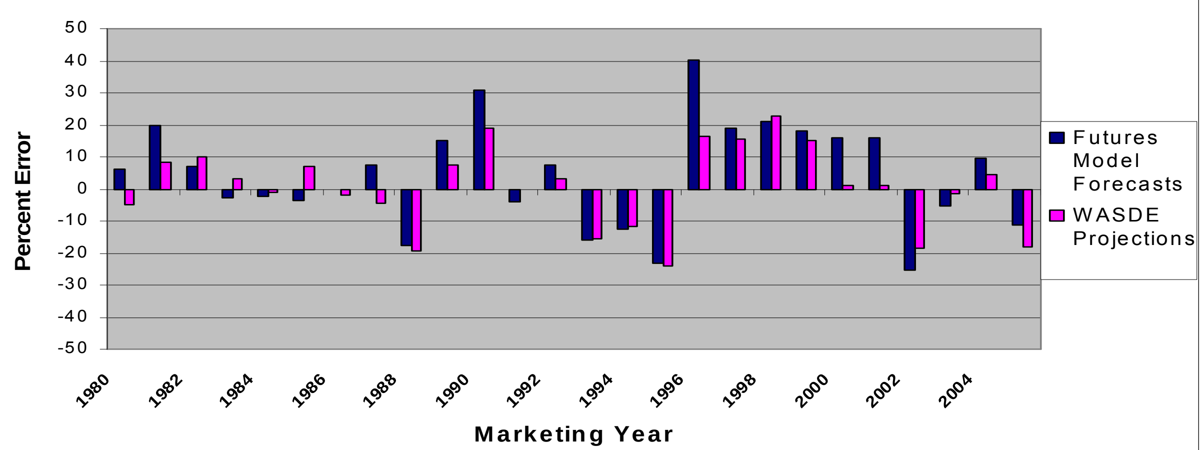


Table 3. Forecast Accuracy Statistics for the Futures Model Forecasts and WASDE Projections of the Season-Average Price Received for Corn, Soybeans, and Wheat, Marketing Years 1980 through 2005.

Commodity and Forecast Periods	Forecast methods: Futures Mean Error	Futures Mean Absolute Error	Futures Mean Squared Error	Futures Mean Percent Error	Futures Mean Absolute Percent Error	Futures Root Mean Squared Percent Error	WASDE Mean Error	WASDE Mean Absolute Error	WASDE Mean Squared Error	WASDE Mean Percent Error	WASDE Mean Absolute Percent Error	WASDE Root Mean Squared Percent Error
Corn	Dollars per bushel			Percent			Dollars per bushel			Percent		
May	0.16	0.33	0.1757	8.5	14.6	17.9	-0.06	0.32	0.1443	-1.1	13.5	16.2
June	0.13	0.32	0.1589	7.2	13.8	17.0	-0.03	0.31	0.1370	-0.1	13.2	15.8
July	0.10	0.28	0.1484	4.9	11.8	16.5	0.01	0.27	0.1019	1.2	11.3	13.6
August	0.05	0.21	0.0707	2.7	9.1	11.4	0.05	0.21	0.0654	2.7	8.8	10.9
September	0.03	0.19	0.0558	1.4	7.8	10.1	0.06	0.19	0.0529	2.5	8.1	9.8
October	0.01	0.15	0.0365	0.5	6.3	8.2	0.03	0.17	0.0402	1.4	7.2	8.6
November	0.01	0.11	0.0246	0.6	4.9	6.7	0.01	0.15	0.0351	0.1	6.0	8.0
December	-0.02	0.10	0.0154	-0.6	4.1	5.3	0.00	0.12	0.0254	-0.3	5.1	6.8
January	0.00	0.09	0.0135	0.2	3.7	5.0	0.01	0.09	0.0148	0.4	3.8	5.2
February	0.01	0.07	0.0092	0.5	3.1	4.1	0.01	0.08	0.0109	0.4	3.2	4.5
March	0.01	0.08	0.0076	0.7	3.3	3.7	0.01	0.06	0.0066	0.4	2.7	3.5
April	0.03	0.06	0.0060	1.2	2.8	3.3	0.02	0.06	0.0054	0.8	2.3	3.1
May	0.02	0.06	0.0048	1.0	2.5	3.0	0.02	0.05	0.0040	0.8	2.0	2.7
June	0.02	0.04	0.0026	0.8	1.9	2.2	0.02	0.04	0.0030	0.7	1.8	2.4
July	0.01	0.03	0.0017	0.5	1.5	1.8	0.01	0.03	0.0016	0.5	1.2	1.7
August	0.00	0.02	0.0010	0.2	1.0	1.3	0.01	0.02	0.0013	0.5	0.9	1.5
Soybeans												
May	0.23	0.80	0.8906	5.2	13.5	15.9	-0.19	0.70	0.8412	-2.3	11.2	15.5
June	0.16	0.71	0.7474	3.7	11.6	14.6	-0.18	0.67	0.8178	-2.1	10.6	15.3
July	0.13	0.66	0.6723	2.7	10.7	13.8	-0.14	0.57	0.6166	-1.6	9.2	13.3
August	0.02	0.44	0.3846	0.5	7.0	10.5	-0.02	0.45	0.4191	0.1	7.3	10.9
September	0.10	0.42	0.3056	1.7	6.8	9.3	0.08	0.42	0.3393	1.4	6.6	9.8
October	0.02	0.39	0.2032	0.2	6.3	7.6	0.03	0.39	0.2544	0.4	6.4	8.5
November	0.02	0.26	0.1271	0.2	4.1	6.0	0.01	0.36	0.2284	0.0	5.7	8.1
December	-0.03	0.16	0.0464	-0.4	2.8	3.6	0.02	0.27	0.1456	0.2	4.5	6.4
January	-0.02	0.13	0.0263	-0.3	2.1	2.7	-0.01	0.21	0.0644	-0.2	3.5	4.3
February	-0.05	0.11	0.0231	-0.9	1.9	2.6	-0.02	0.17	0.0394	-0.4	2.8	3.4
March	-0.01	0.09	0.0132	-0.2	1.5	1.9	-0.05	0.11	0.0238	-0.9	1.9	2.6
April	0.02	0.08	0.0130	0.3	1.3	1.9	-0.03	0.09	0.0133	-0.5	1.5	1.9
May	0.04	0.07	0.0097	0.5	1.2	1.7	-0.01	0.07	0.0084	-0.2	1.2	1.5
June	0.02	0.06	0.0062	0.4	1.0	1.3	0.00	0.06	0.0071	-0.1	0.9	1.4
July	0.02	0.05	0.0063	0.4	0.9	1.3	0.01	0.06	0.0082	0.2	1.0	1.5
August	0.02	0.04	0.0036	0.3	0.6	1.0	0.01	0.05	0.0053	0.2	0.8	1.2
Wheat												
May	0.11	0.46	0.3501	4.2	13.7	18.0	0.00	0.35	0.1919	0.5	10.2	13.3
June	0.04	0.36	0.1928	1.6	10.9	13.3	0.00	0.33	0.1638	0.4	9.7	12.3
July	-0.04	0.27	0.1017	-1.2	8.3	9.7	-0.05	0.23	0.0921	-1.5	7.0	9.2
August	-0.02	0.21	0.0592	-0.6	6.3	7.4	-0.03	0.19	0.0597	-1.2	5.5	7.4
September	-0.01	0.15	0.0346	0.0	4.6	5.6	-0.03	0.14	0.0318	-1.2	4.2	5.4
October	0.01	0.14	0.0286	0.8	4.3	5.1	-0.01	0.11	0.0200	-0.5	3.3	4.3
November	0.01	0.09	0.0153	0.5	2.9	3.8	0.00	0.09	0.0148	-0.1	2.7	3.7
December	-0.01	0.06	0.0056	-0.3	2.0	2.3	0.01	0.07	0.0093	0.0	2.1	2.9
January	0.00	0.06	0.0055	0.3	2.0	2.3	0.01	0.05	0.0042	0.3	1.6	2.0
February	0.00	0.05	0.0037	0.3	1.7	1.8	0.01	0.04	0.0029	0.4	1.3	1.6
March	0.00	0.04	0.0029	0.1	1.4	1.6	0.00	0.03	0.0014	0.1	0.9	1.2
April	0.00	0.03	0.0017	0.0	0.9	1.3	0.00	0.02	0.0010	0.0	0.7	1.0
May	0.01	0.03	0.0013	0.2	0.8	1.1	0.01	0.02	0.0010	0.2	0.6	0.9

The shaded area means the statistic for that particular forecast method had a lower mean squared error or root mean squared percentage error than the alternative forecast method.

Table 4. Computation of Modifed Diebold Mariano (MDM) test statistic used to determine statistical difference between the futures model forecasts and WASDE projections

Commodity & Forecast Periods	$[(n-1)]^{1/2}$	X $\left[\hat{v}(\bar{d})\right]^{-1/2}$	$\bar{d}$	= MDM statistic		p-Values
Corn						
May	5.000	0.228	0.0314	0.691		0.496
June	5.000	0.202	0.0219	0.544		0.592
July	5.000	0.200	0.0465	1.164		0.255
August	5.000	0.056	0.0053	0.475		0.639
September	5.000	0.067	0.0028	0.210		0.835
October	5.000	0.061	-0.0037	-0.307		0.761
November	5.000	0.042	-0.0106	-1.267		0.217
December	5.000	0.035	-0.0100	-1.435		0.164
January	5.000	0.015	-0.0013	-0.451		0.656
February	5.000	0.015	-0.0018	-0.587		0.562
March	5.000	0.010	0.0010	0.510		0.614
April	5.000	0.008	0.0005	0.357		0.724
May	5.000	0.007	0.0008	0.609		0.548
June	5.000	0.005	-0.0004	-0.379		0.708
July	5.000	0.004	0.0001	0.146		0.885
August	5.000	0.004	-0.0003	-0.401		0.692
Soybeans						
May	5.000	0.736	0.0494	0.336		0.740
June	5.000	0.748	-0.0704	-0.470		0.642
July	5.000	0.538	0.0557	0.518		0.609
August	5.000	0.269	-0.0345	-0.640		0.528
September	5.000	0.287	-0.0337	-0.586		0.563
October	5.000	0.228	-0.0511	-1.120		0.273
November	5.000	0.282	-0.1013	-1.795		0.085
December	5.000	0.227	-0.0992	-2.188	**	0.038
January	5.000	0.069	-0.0380	-2.766	**	0.011
February	5.000	0.046	-0.0163	-1.760		0.091
March	5.000	0.049	-0.0106	-1.073		0.294
April	5.000	0.036	-0.0003	-0.041		0.967
May	5.000	0.010	0.0014	0.710		0.484
June	5.000	0.016	-0.0010	-0.305		0.763
July	5.000	0.011	-0.0019	-0.837		0.411
August	5.000	0.012	-0.0017	-0.699		0.491
Wheat						
May	5.000	0.497	0.1582	1.593		0.124
June	5.000	0.175	0.0290	0.831		0.414
July	5.000	0.135	0.0096	0.354		0.727
August	5.000	0.087	-0.0004	-0.024		0.981
September	5.000	0.050	0.0028	0.284		0.779
October	5.000	0.039	0.0086	1.108		0.278
November	5.000	0.027	0.0005	0.084		0.933
December	5.000	0.014	-0.0038	-1.335		0.194
January	5.000	0.007	0.0013	0.969		0.342
February	5.000	0.006	0.0008	0.696		0.493
March	5.000	0.004	0.0015	1.731		0.096
April	5.000	0.003	0.0007	1.182		0.248
May	5.000	0.002	0.0003	0.692		0.496

** Reject null hypothesis at the 5 percent (critical t = 2.06) signifiance level

Table 5. Computation of the Modifed Diebold-Mariano (MDM) Test Statistic Used for the Forecast Encompassing Test of Pricing Efficiency

Commodity & Forecast Periods	$[(n-1)]^{1/2}$	X	$\left[\hat{V}(\bar{d})\right]^{-1/2}$	$\bar{d}$	=	MDM statistic		*p*-Values
Corn								
May	5.000		0.149	0.064		2.134	**	0.043
June	5.000		0.106	0.055		2.590	**	0.016
July	5.000		0.127	0.059		2.329	**	0.028
August	5.000		0.040	0.020		2.542	**	0.018
September	5.000		0.043	0.019		2.269	**	0.032
October	5.000		0.034	0.013		1.865		0.074
November	5.000		0.014	0.003		1.163		0.256
December	5.000		0.016	0.003		0.881		0.387
January	5.000		0.011	0.004		1.876		0.072
February	5.000		0.012	0.003		1.370		0.183
March	5.000		0.006	0.004		3.178	*	0.004
April	5.000		0.004	0.003		3.232	*	0.003
May	5.000		0.006	0.003		2.289	**	0.031
June	5.000		0.004	0.002		2.153	**	0.041
July	5.000		0.003	0.002		3.163	*	0.004
August	5.000		0.002	0.001		2.480	**	0.020
Soybeans								
May	5.000		0.566	0.203		1.793		0.085
June	5.000		0.576	0.130		1.126		0.271
July	5.000		0.369	0.141		1.914		0.067
August	5.000		0.283	0.050		0.876		0.389
September	5.000		0.154	0.028		0.913		0.370
October	5.000		0.121	0.011		0.455		0.653
November	5.000		0.090	-0.011		-0.628		0.536
December	5.000		0.045	-0.007		-0.805		0.428
January	5.000		0.031	-0.006		-0.984		0.335
February	5.000		0.035	0.004		0.536		0.596
March	5.000		0.013	0.007		2.593	**	0.016
April	5.000		0.017	0.005		1.565		0.130
May	5.000		0.006	0.004		2.819	*	0.009
June	5.000		0.009	0.002		1.102		0.281
July	5.000		0.005	0.001		0.549		0.588
August	5.000		0.006	0.001		0.489		0.629
Wheat								
May	5.000		0.347	0.123		1.767		0.090
June	5.000		0.091	0.042		2.324	**	0.029
July	5.000		0.087	0.031		1.772		0.089
August	5.000		0.051	0.012		1.231		0.230
September	5.000		0.030	0.012		1.926		0.066
October	5.000		0.028	0.014		2.567	**	0.017
November	5.000		0.018	0.006		1.762		0.090
December	5.000		0.006	0.002		1.872		0.073
January	5.000		0.005	0.003		3.175	*	0.004
February	5.000		0.004	0.002		2.533	**	0.018
March	5.000		0.004	0.002		2.803	*	0.010
April	5.000		0.003	0.001		2.698	**	0.012
May	5.000		0.002	0.001		2.796	*	0.010

* Reject null hypothesis at the 1 percent (critical t = 2.78) significance level
** Reject null hypothesis at the 5 percent (critical t = 2.06) significance level

Figure 2a. Value of d_t for Forecast Difference and Forecast Encompassing Tests; May Forecast Period for Corn

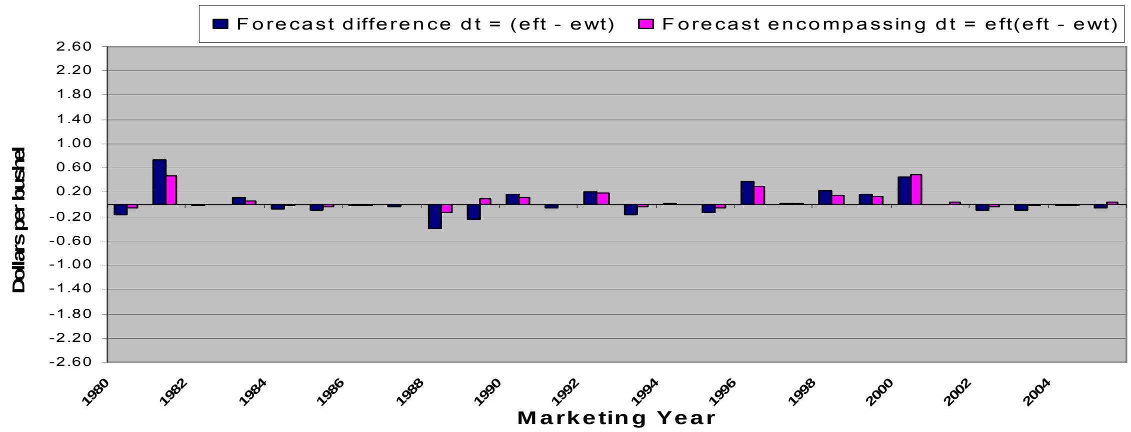


Figure 2b. Value of d_t for Forecast Difference and Forecast Encompassing Tests; May Forecast Period for Soybeans

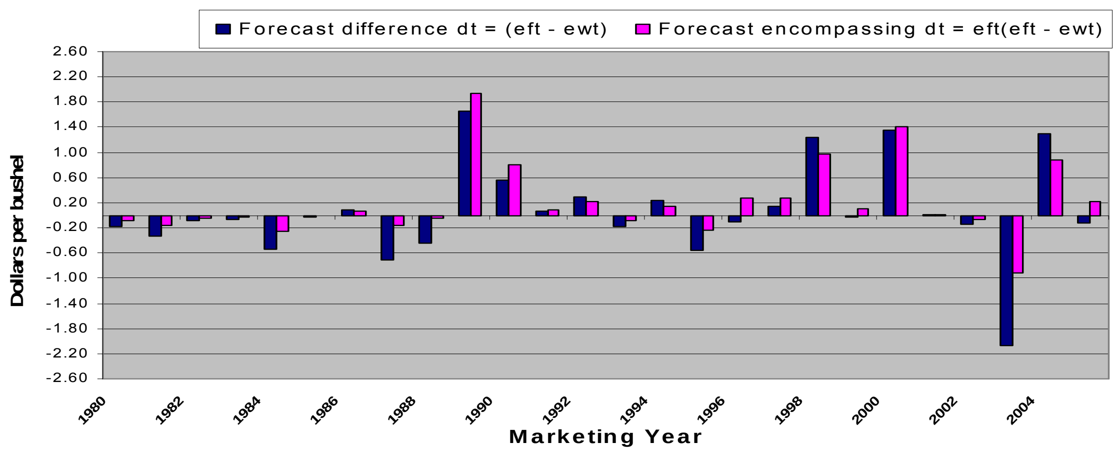


Figure 2c. Value of d_t for Forecast Difference and Forecast Encompassing Tests; May Forecast Period for Wheat